International Review of Financial Analysis 95 (2024) 103426

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Trading strategies and Financial Performances: A simulation approach

Alessio Emanuele Biondo [a], Laura Mazzarino [b,*], Alessandro Pluchino [b,c]

[a] Department of Economics and Business, University of Catania, Corso Italia, 55, 95129 Catania, Italy
[b] Department of Physics and Astronomy, University of Catania, Via S. Sofia, 64, 95123 Catania, Italy
[c] INFN, Catania, Italy

ARTICLE INFO

JEL classification:
C63
G11
G12
G17

Keywords:
Sharpe ratio
Expected Shortfall
Portfolio performance
Order-book
Simulations

ABSTRACT

This paper presents a comparative analysis of three major approaches to portfolio strategies: the maximization of the Sharpe ratio, the minimization of the Expected Shortfall and "zero–intelligence" trading. Data from financial time series and from a simulated order-book are used to analyse how various strategies affect investors' portfolio performance and volatility. Results show, firstly, that the superiority of technical and analytical approaches over a random strategy is not obvious. Secondly, that strategies with lower and less risky profits may reveal preferable to those with higher returns and risk. Balancing this trade-off is crucial for stable financial growth.

1. Introduction

Selecting the optimal allocation of funds across available investments is one of the main goals of financial traders. Portfolio Selection Theory was pioneered by Markowitz (1952), who developed a mean–variance model that allowed investors to build optimal portfolios. To do so, traders need to identify a portfolio combination of assets, by determining their weights, which either maximizes overall returns given a certain level of risk or minimizes risk given a certain level of returns. Despite its scientific merit, this approach is not widely adopted by traders due to its limitations, which include the substantial volume of data required, the creation of poorly diversified portfolios, and the unrealistic hypothesis it relies upon, such as the assumption that all investors are risk–averse and do not suffer from informational asymmetries. Following the work of Markowitz, several alternatives have been introduced to overcome these shortcomings. The first contribution in this direction is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965) and Mossin (1966). In this model, there is a drastic reduction in the required data to obtain optimal portfolios, thanks to Sharpe's observations on the relationship between stock prices and the performance of market indices. More diversified portfolios, on the other hand, can be found through the Black and Litterman model (introduced in 1991, 1992 and later explored by Satchell and Scowcroft (2000), Meucci (2006), Idzorek (2007) and Walters et al. (2014), among others). This model starts with a CAPM–derived portfolio and introduces a method to combine it with analysts' market opinions (views) to obtain new distributions of asset returns and a modified covariance matrix.

Another limitation of the Markowitz's approach is the assumption of no transaction costs and taxes, leading to the construction of suboptimal portfolios. Many models have been proposed to incorporate these transaction costs into the portfolio optimization problem. For example, Yoshimoto (1996) used a nonlinear programming technique, Chen, Fabozzi, and Huang (2010) considered transaction costs paid at the end of the planning horizon, and Brown and Smith (2011) applied heuristic trading strategies to address this issue. Markowitz's model also tends to maximize estimation error (Chopra & Ziemba, 1993), meaning that there is a high probability of making errors in calculating the inputs of the model, thus significantly impacting the resulting portfolio. Several strategies have been proposed to mitigate these errors, such as imposing constraints on the minimum (or maximum) weight of an asset in the portfolio or forbidding short positions. Another method is the robust portfolio optimization (see Xidonas, Steuer, & Hassapis, 2020 for a recent and extensive review) which differs from the classical approach by considering uncertainty in inputs. Its goal is to identify an asset allocation strategy that performs optimally even in worst-case scenarios of uncertain inputs.

In Markowitz's framework the measure of risk used is the variance (standard deviation). While this can be a valuable approach for assessing risk in specific situations, it does have certain limitations when

* Corresponding author.
E-mail address: laura.mazzarino@phd.unict.it (L. Mazzarino).

https://doi.org/10.1016/j.irfa.2024.103426
Received 10 November 2023; Received in revised form 31 January 2024; Accepted 19 February 2024
Available online 5 July 2024

dealing with non-normal distributions, which exhibit asymmetry and fat-tailed returns. It treats positive and negative returns equally, even though investors are more concerned about losses. Moreover, it does not effectively capture the risk associated with extreme "tail events", such as financial crises which can have significant impacts. During the years, many other risk measure have been proposed; among them, one of the most popular in financial studies is the Value at Risk (VaR), which estimates the maximum potential loss of an investment with a certain level of confidence and within a given time period. This measure has been employed for portfolio optimization problems by various authors, including Campbell, Huisman, and Koedijk (2001), Gaivoronski and Pflug (2005) and Benati and Rizzi (2007). However, the VaR also manifests some mathematical limitations, such as the lack of subadditivity and convexity (Artzner, Delbaen, Eber, & Heath, 1997, 1999). Thus, another risk measure called the Expected Shortfall (henceforth, ES) gained popularity. The ES, also known as Conditional Value at Risk (CVaR), represents the average expected loss beyond a critical point, i.e., the VaR level. It provides a more comprehensive view of risk because it is able to capture both the probability and magnitude of large losses and, unlike the VaR, it is subadditive, convex and a coherent risk measure (Pflug, 2000). Over the years, various models have been developed to use the ES for portfolio optimization, particularly to find the portfolio minimizing it. For example, Rockafellar et al. (2000) showed that CVaR can be effectively minimized using Linear Programming and Nonsmooth Optimization algorithms. Krokhmal, Palmquist, and Uryasev (2002) proposed an alternative approach to maximize the expected returns under ES constraints.

In recent times, many machine learning–based algorithms have also been applied to portfolio selection analysis. For instance, the work of Fernández and Gómez (2007) and Freitas, De Souza, and De Almeida (2009) employed a neural network model, while Golmakani and Alishah (2008) proposed a heuristic methods based on an artificial immune system. More recently, Ban, El Karoui, and Lim (2018) used a performance–based regularization methodology, which helps in mitigating estimation errors.

The portfolio optimization techniques reviewed here do not include all the methodologies proposed since Markowitz's seminal work. Given the vast array of existing methods, the aim of this work is to present a framework to compare various optimization techniques. In particular, here we provide a comparison between three alternative approaches: the maximization of the Sharpe ratio, the minimization of the Expected Shortfall, and a "zero–intelligence" trading approach (as in Biondo, Pluchino, & Rapisarda, 2013a). The first method is based on Markowitz's idea and involves the maximization of the Sharpe ratio (Sharpe, 1966, 1994), which is a performance index of portfolios, computed by dividing the expected portfolio return by its standard deviation. This ratio was initially proposed by Roy (1952), who introduced a portfolio evaluation method based on a risk-return ratio, and later adapted by Sharpe to Markowitz's framework.

To evaluate these potential optimization strategies, we build an agent-based model (ABM) which simulates a financial market populated by a community of interacting heterogeneous agents, all aiming to optimize their portfolios. Given their ability in emphasizing the role of heterogeneity and interactions among agents, ABMs have been extensively employed in the study of financial markets. Comprehensive reviews of these models can be found in LeBaron (2006), Hommes (2006) Dieci and He (2018), and more recently, in Axtell and Farmer (2022).

As mentioned earlier, the heterogeneity in our model is modelled with the various rules that traders follow to determine the weights of their optimal portfolios. However, to increase this heterogeneity and to compare a broader range of techniques, five different strategies have been employed for computing price expectations, which are then used in the computation of the Sharpe ratio. Specifically, we adopt five acknowledged behavioural rules: fundamentalist, chartist, the Moving–Average–Convergence–Divergence - MACD; the Relative Strength Index - RSI (Wilder, 1978) and the Rate of Change - ROC (see Murphy, 1999 for a detailed description of these techniques). Some studies have been conducted to compare these technical rules. Among them, Chiang, Ke, Liao, and Wang (2012) examined nine distinct strategies, including the RSI, and juxtaposed them with the traditional buy-and-hold approach. Pätäri and Vilska (2014) inspected the performance of dual moving average crossover portfolios and Hung (2016) provided a comparative analysis of various MACD strategies.

Nevertheless, the first two strategies are the most commonly used in financial literature, dating back to Zeeman's work in Zeeman (1974), where the author proposed a model that differentiated fundamentalists from chartists. These strategies have primarily been employed in the analysis of how the interaction among these heterogeneous agents leads to instability in the financial market, as seen in the works of Beja and Goldman (1980), Day and Huang (1990), and others. Frankel and Froot (1990) applied this distinction to study the foreign exchange market and Chiarella (1992) presented a model of asset price dynamics with these two types of agents. In Brock and Hommes (1998) traders can also switch between the two different behaviours, influenced by profits and imitation. Westerhoff and Reitz (2003) analysed the cyclical movements in exchange rates. Tramontana, Westerhoff, and Gardini (2015) introduced a model with some traders who are constantly active and others who only enter the market if certain thresholds are crossed. More recently, Boutouria, Hamad, and Medhioub (2020) searched anomalies in the French market caused by the heterogeneity between fundamentalists and chartists.

Most models in the literature focus on analysing a single market for one risky asset. Conversely, in our study, traders must decide how to allocate their wealth between different assets in separate markets. Some research explored the joint dynamics of multiple asset markets, as seen in the work of Westerhoff (2004). In this study, a multi-asset market dynamic was presented, allowing traders to switch not only between strategies (fundamentalists and chartists) but also across different markets. A few years later, in Westerhoff and Dieci (2006), the authors extended the earlier model to analyse the impact of transaction taxes. Later, in Chiarella, Dieci, and He (2007), a dynamic model is presented in which heterogeneous traders invest in two risky assets and in a risk-free one. Related to our work, there are papers adopting ABMs to portfolio optimization problems, such as the work by Feldman (2010), in which agents make allocation decisions among two risky assets and a risk-free asset using Markowitz's framework. In Orito, Kambayashi, Tsujimura, and Yamamoto (2011) and Biondo, Mazzarino, and Rossello (2021), a single portfolio optimization strategy was employed. Both studies employed the maximization of performance indices, such as the Information ratio (Goodwin, 1998) and the Sharpe ratio.

The present paper advances two approaches. In the first one, simulations are conducted by using exogenous prices, deriving from real data of selected financial assets. In the second one, prices are endogenous and emerge from the interaction of agents in a truly operative order-book. The earliest order-driven market models were quite simple, such as the one presented in Stigler (1963), which included only unit volume limit orders randomly placed in the book, and in Bak, Paczuski, and Shubik (1997), where noise traders could exchange one share of stock at a time. Over time, much more realistic models have been introduced, as seen in Maslov (2000), where both limit and market orders were modelled. In Chiarella and Iori (2002), they presented an auction market model with limit and market orders, introducing behavioural heterogeneity (fundamentalists and chartists). Our model is based on Chiarella and Iori (2002), further developed in Chiarella, Iori, and Perelló (2009), and Biondo (2018) who analysed the impact on the market volatility of traders' personal characteristics (e.g., their behavioural rules) and of microstructure, such as the time validity of limit orders and the length of the order-book.

Our paper introduces an innovative approach to modelling order-book dynamics. Unlike conventional models that usually include only fundamentalists, chartists, and random traders, ours implements a wider range of trading behaviours. Additionally, two order-books are modelled, and agents simultaneously place orders in both of them in order to construct their optimal portfolios. Previous studies on multi-asset artificial markets include Cincotti, Focardi, Marchesi, and Raberto (2003), which analyses the long-term performance of various trading strategies and Consiglio, Lacagnina, and Russino (2005), presenting a continuous auction order-driven model with multiple risky assets, but with agents employing the same trading strategy. In a more recent work by Ponta, Raberto, and Cincotti (2011), they replicate the model presented in Cincotti et al. (2003) but with random traders, demonstrating that the model can still replicate stylized facts.

In modelling artificial markets, it is crucial to create models that mimic real-world behaviour, replicating the key statistical characteristics of real financial data, i.e., stylized facts of financial series, widely described by Cont (2001), Lux and Alfarano (2016) and reviewed in Chakraborti, Toke, Patriarca, and Abergel (2011). Several ABMs studies are focused on the reproduction of financial markets characteristics. Notable examples include Alfarano, Lux, and Wagner (2005), Cont and Bouchaud (2000), Lux and Marchesi (2000) and Alfarano and Lux (2007). Our model is able to replicate the main stylized facts of the financial returns, i.e, the presence of fat tails of the probability density functions of returns (Gopikrishnan, Plerou, Amaral, Meyer, & Stanley, 1999; Mandelbrot, 1963), the absence of autocorrelation (Cont, Potters, & Bouchaud, 1997; Pagan, 1996) and the presence of volatility clustering (Mandelbrot, 1963).

The aim of this paper is to advance a comparison among several technical and analytical strategies of portfolio optimization, based on different models of expectations formation, to assess their performances. Our results shed new light on the positive correlation between returns and risk, suggesting that a random approach to financial investments can be preferable compared to more remunerative but much more riskier alternatives.

The rest of the paper is organized as follows: Section 2 contains the description of model; Section 3 shows results of simulations; Section 4 presents concluding remarks.

2. The model

Our model adopts two complementary approaches to compare the performance of financial trading strategies. The first one is based on the empirical dataset of financial assets within a back-testing framework, in which the trading activity of agents reacting to exogenous prices is simulated by disclosing prices time step by time step. The second one is based on a truly operative order-book model, in which prices are generated endogenously by negotiations of traders.

2.1. Trading strategies

Both in the back-testing model and in the order-book model agents will be endowed with one of three main strategies: (1) maximizing the Sharpe ratio, (2) minimizing the Expected Shortfall, and (3) adopting a "zero–intelligence" approach.

2.1.1. Sharpe ratio maximization

The mean–variance optimization, based on Markowitz's theory, provides a tool for the selection of assets in the portfolio composition. Each trader h decides the allocation of her wealth among assets $A_1, A_2, \dots, A_n$, $(n \geq 2)$, aiming at obtaining the highest return at the smallest risk, by setting the weights $w_{h,i}$, $i = 1, 2, \dots, n$, i.e., the proportion of wealth invested in each security i, thus creating a portfolio, denoted as $\mathbf{w}_h = (w_{h,1}, w_{h,2}, \dots, w_{h,n})$. Let $\boldsymbol{\mu}_h = \left[\mu_{h,1}, \mu_{h,2}, \dots, \mu_{h,n}\right]^T$ be the $1 \times n$ vector of expected returns and $\boldsymbol{\Omega} = (\sigma_{ij})$ the $n \times n$ covariance matrix of assets, such that $\sigma_{ij} = \sigma_i^2$ if $i = j$ and $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$ if $i \neq j$, being ρ_{ij} the correlation coefficient between A_i and A_j. Thus, $\mathrm{E}\left[\mathbf{w}_h\right] = \sum_{i=1}^n w_{h,i}\mu_{h,i} = \left[\boldsymbol{\mu}_h\right]^T \mathbf{w}_h$ and $\mathrm{Var}\left[\mathbf{w}_h\right] = \sum_{i=1}^n \sum_{j=1}^n \rho_{ij}\sigma_i\sigma_j w_{h,i} w_{h,j} = \mathbf{w}_h^T \boldsymbol{\Omega} \mathbf{w}_h$ are the expected return and the variance of portfolio $\mathbf{w}_h$, respectively. Following Cornuejols and Tütüncü (2007), we assume that the set of feasible portfolios is defined as $\mathcal{W} := \{\mathbf{w} : \mathbf{A}\mathbf{w} = \mathbf{b}, \mathbf{C}\mathbf{w} \geq \mathbf{d}\}$, being $\mathbf{A}$ an $m \times n$ matrix, $\mathbf{b}$ an $m \times 1$ vector, $\mathbf{C}$ a $p \times n$ matrix and $\mathbf{d}$ a $p \times 1$ vector, and that $\sum_{i=1}^n w_{h,i} = 1$, $\forall i$ and h.

In general, mean–variance problems for $\mathbf{w} \in \mathcal{W}$ can be stated in different ways, according to the chosen configuration for the objective and the constraint functions. For instance, the portfolio variance, $\mathbf{w}^T \boldsymbol{\Omega} \mathbf{w}$, can be minimized subject to the constraint of a given return R, i.e., $\boldsymbol{\mu}^T \mathbf{w} \geq R$. Alternatively, the efficient portfolio can be defined as the one maximizing the return, $\boldsymbol{\mu}^T \mathbf{w}$, subject to the constraint of a given variance σ^2, i.e., $\mathbf{w}^T \boldsymbol{\Omega} \mathbf{w} \leq \sigma^2$. Finally, a risk-adjusted return can be considered, in such a way that the expected return is weighted by means of a risk-aversion constant (α), and the problem would consist in the maximization of $\boldsymbol{\mu}^T \mathbf{w} - (\alpha/2)\mathbf{w}^T \boldsymbol{\Omega} \mathbf{w}$.

One of the most acknowledged measures of portfolio performance is the Sharpe ratio, which computes the excess return of a given portfolio with respect to a risk-free return rate $\mu_0 \geq 0$, per unit of risk.

$$S = \frac{\boldsymbol{\mu}^T \mathbf{w} - \mu_0}{(\mathbf{w}^T \boldsymbol{\Omega} \mathbf{w})^{1/2}}$$

The combination of different profiles of returns and risk of portfolios is usually represented by the so-called *capital allocation line* in the graph where axes measure standard deviation and returns, with the natural assumption that $\mu_i > \mu_0$, $\forall i$. The capital allocation line with the smallest slope is built with the so-called tangent portfolio w_S that maximizes the Sharpe ratio, as explained by Campbell, Lo, MacKinlay, and Whitelaw (1998). The maximization of S is not straightforward, since it is possibly a non-convex optimization because of non-concavity of the objective. Cornuejols and Tütüncü (2007) show that by choosing an opportune scale factor $\boldsymbol{\kappa} > 0$, it is possible to construct an equivalent convex quadratic programming problem, which basically minimizes an objective of the type $\tilde{\mathbf{w}}^T \boldsymbol{\Omega}^{-1} \tilde{\mathbf{w}}$, with $\mathbf{w} = \tilde{\mathbf{w}}/\boldsymbol{\kappa}$, under the stringent assumption that there exists a feasible portfolio $\mathbf{w}^* \in \mathcal{W}$ with $\boldsymbol{\mu}^T \mathbf{w}^* > \mu_0$. Assuming $\mu_0 = 0$ and denoting by $\mathbf{1}^T$ a $1 \times n$ vector of 1s, the tangent portfolio of each trader h, with two risky assets is defined as

$$\mathbf{w}_h = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{\mu}_h}{\mathbf{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{\mu}_h} \tag{1}$$

Thus, in our model, weights of the tangent portfolio maximizing the Sharpe ratio are computed by each trader h accordingly. Following Ruppert (2004), for the $n = 2$ case values correspond to

$$\begin{aligned} w_{h,1} &= \frac{\mu_{h,1}\sigma_2^2 - \mu_{h,2}\rho_{12}\sigma_1\sigma_2}{\mu_{h,1}\sigma_2^2 + \mu_{h,2}\sigma_1^2 - \left(\mu_{h,1} + \mu_{h,2}\right)\rho_{12}\sigma_1\sigma_2} \quad \text{and} \\ w_{h,2} &= 1 - w_{h,1} = \frac{\mu_{h,2}\sigma_1^2 - \mu_{h,1}\rho_{12}\sigma_1\sigma_2}{\mu_{h,1}\sigma_2^2 + \mu_{h,2}\sigma_1^2 - \left(\mu_{h,1} + \mu_{h,2}\right)\rho_{12}\sigma_1\sigma_2} \end{aligned} \tag{2}$$

Despite notation has been simplified above, values for $w_{h,1}$ and $w_{h,2}$ are in fact obtained at each time step t as $w_{h,1,t}$ and $w_{h,2,t}$. Traders correspondingly allocate their wealth, computed as $Y_{h,t} = (1 + \boldsymbol{\mu}_{h,t-1}^T \mathbf{w}_{h,t-1})$ $Y_{h,t-1}$, with $Y_{h,0} = \bar{Y}$, $\forall h$, as specified below. Quantities of assets in the portfolio of trader h are $q_{h,i,t} = w_{h,i,t}\, Y_{h,t-1}/p_{i,t}$, $\forall t$, with $i = 1, 2$, being $p_{i,t}$ the market price of the asset i. Five different mechanisms of expectations formation have been implemented to compute expected prices, thus implying expected returns $\mu_{h,i,t}$, according to the typology of the trader, as it follows:

(1) Fundamentalist traders:
Fundamentalists believe that the most important factor in understanding the movements of an asset price over time is its fundamental value (FV$_t$). In their view, FV$_t$ represents the true value of the asset, taking into account all important informations, such as dividend yields. In our model, when running the back-testing model, FV$_t$ is computed as the average of all prices, in order to represent the whole set of information available to all traders;

instead, when running the order-book model, FV_t is modelled as an exogenous random variable, defined as:

$$\text{FV}_t = \text{FV}_{t-1} + \mathbb{D}_t \tag{3}$$

where $\text{FV}_0 = \bar{\phi}$ and $\mathbb{D}_t \sim \mathcal{N}(0, \sigma_F)$. In both cases, fundamentalists compute their expected price as:

$$_{\text{FUND}}p_t^{exp} = \text{FV}_t \tag{4}$$

(2) Chartist traders:
Chartists are technical analysts who decide their trading strategy by observing historical price patterns and movements. Each of them calculates a reference value RV_t by taking the mean of prices within a time window of length T_w, i.e., $\text{RV}_t = \frac{1}{T_w}\sum_{j=t-T_w}^{t} p_j$ and computes the expected price as:

$$_{\text{CHART}}p_t^{exp} = p_t - (\text{RV}_t - p_t) = 2p_t - \text{RV}_t \tag{5}$$

(3) MACD traders:
The Moving–Average–Convergence–Divergence (henceforth MACD) uses exponential moving averages, EMA^d, related to time intervals of length d. In our model, the difference is between the averages over $d = 12$ and $d = 26$ days:

$$\text{MACD} = \text{EMA}^{12} - \text{EMA}^{26} \tag{6}$$

where $\text{EMA}_t^d = \text{EMA}_{t-1}^d + w\left(p_t - \text{EMA}_{t-1}^d\right)$, with $\text{EMA}_0^d = \sum_{i=t-d}^{t} p_i/d$, and $w = \frac{2}{d+1}$.
The so-called MACD–Divergence strategy, is based on divergences between the time series of the asset price and its related MACD series within a specified window of time. If both series have their two highest (lowest) points pointing in the same direction as the trend in that window, there will not be a divergence. Otherwise there will be a divergence. Let α_S represent the slope of the trend derived from the time series and α_M the slope of the line connecting the two local extrema. If a divergence exists, the expected price of MACD traders is computed according to:

– if the price series, in the windowed time period, is increasing:

$$\begin{cases} \alpha_S < 0 \ \wedge \ \alpha_M > 0 \ \rightarrow \ _{\text{MACD}}p_t^{\text{exp}} = p_t + \alpha_M \\ \alpha_S > 0 \ \wedge \ \alpha_M < 0 \ \rightarrow \ _{\text{MACD}}p_t^{\text{exp}} = p_t - \alpha_M \end{cases} \tag{7}$$

– if the price series, in the windowed time period, is decreasing:

$$\begin{cases} \alpha_S < 0 \ \wedge \ \alpha_M > 0 \ \rightarrow \ _{\text{MACD}}p_t^{\text{exp}} = p_t - \alpha_M \\ \alpha_S > 0 \ \wedge \ \alpha_M < 0 \ \rightarrow \ _{\text{MACD}}p_t^{\text{exp}} = p_t + \alpha_M \end{cases} \tag{8}$$

(4) RSI traders:
This strategy is based on the computation of the Relative Strength Index (Wilder, 1978):

$$\text{RSI} = 100 - \frac{100}{1 + \text{RS}} \tag{9}$$

where $\text{RS} = \mu_\uparrow/\mu_\downarrow$, being $\mu_\uparrow = (1/T_w)\sum_{k=1}^{T_w} p_k \ \forall p_s > p_{s-1}$ and $\mu_\downarrow = (1/T_w)\sum_{k=1}^{T_w} p_k \ \forall p_s < p_{s-1}$, the average price over all prices increments (decrements) in the considered time window of length T_w. In our simplified version of the model proposed in Murphy (1999), expectations are formed according to the divergence between the trend of the RSI oscillator computed for the entire price series (RSI_p) and the one computed for the windowed period of length T_w (RSI_{T_w}). At each time step, for both oscillators, the two highest and the two lowest local peaks within the past T_w observations are registered, i.e., $\text{RSI}_p^{\text{MAX}_1}$, $\text{RSI}_p^{\text{MAX}_2}$, $\text{RSI}_{T_w}^{\text{MAX}_1}$, $\text{RSI}_{T_w}^{\text{MAX}_2}$, $\text{RSI}_{T_w}^{\text{MIN}_1}$, and $\text{RSI}_{T_w}^{\text{MIN}_2}$. Considering the trend of the windowed time series, delimited by values called respectively $\text{RSI}_{T_w}^0$ and $\text{RSI}_{T_w}^1$, the expectation is formed in case of a divergence, i.e., if $sgn(\text{RSI}_p^{\text{MAX}_1} - \text{RSI}_p^{\text{MAX}_2}) \neq sgn(\text{RSI}_{T_w}^{\text{MAX}_1} - \text{RSI}_{T_w}^{\text{MAX}_2})$, according to the direction of the trend.

– If the trend is decreasing, i.e., $\text{RSI}_{T_w}^0 > \text{RSI}_{T_w}^1$:

$$\begin{cases} \text{if} \ \ \text{RSI}_p^{\text{MAX}_1} < \text{RSI}_p^{\text{MAX}_2} \wedge \text{RSI}_{T_w}^{\text{MAX}_1} > \text{RSI}_{T_w}^{\text{MAX}_2} \rightarrow \ _{\text{RSI}}p^{exp} = p + (\text{RSI}_{T_w}^{\text{MAX}_1} - \text{RSI}_{T_w}^{\text{MAX}_2}) \\ \text{if} \ \ \text{RSI}_p^{\text{MAX}_1} > \text{RSI}_p^{\text{MAX}_2} \wedge \text{RSI}_{T_w}^{\text{MAX}_1} < \text{RSI}_{T_w}^{\text{MAX}_2} \rightarrow \ _{\text{RSI}}p^{exp} = p - (\text{RSI}_{T_w}^{\text{MAX}_1} - \text{RSI}_{T_w}^{\text{MAX}_2}) \end{cases} \tag{10}$$

– If the trend is increasing, i.e., $\text{RSI}_{T_w}^0 < \text{RSI}_{T_w}^1$:

$$\begin{cases} \text{if} \ \ \text{RSI}_p^{\text{MIN}_1} < \text{RSI}_p^{\text{MIN}_2} \wedge \text{RSI}_{T_w}^{\text{MIN}_1} > \text{RSI}_{T_w}^{\text{MIN}_2} \rightarrow \ _{\text{RSI}}p^{exp} = p - (\text{RSI}_{T_w}^{\text{MIN}_2} - \text{RSI}_{T_w}^{\text{MIN}_1}) \\ \text{if} \ \ \text{RSI}_p^{\text{MIN}_1} > \text{RSI}_p^{\text{MIN}_2} \wedge \text{RSI}_{T_w}^{\text{MIN}_1} < \text{RSI}_{T_w}^{\text{MIN}_2} \rightarrow \ _{\text{RSI}}p^{exp} = p + (\text{RSI}_{T_w}^{\text{MIN}_2} - \text{RSI}_{T_w}^{\text{MIN}_1}) \end{cases} \tag{11}$$

(5) ROC traders:
The rate of change (ROC), is the ratio between the current and the previous price, as defined in Eq. (12), and exhibits higher (lower) values during an upward (downward) trend:

$$\text{ROC} = \frac{p_t}{p_{t-1}} \tag{12}$$

At each time step, ROC traders determine their price expectation as a function of ROC:

$$_{\text{ROC}}p_t^{exp} = p_t * \text{ROC} \tag{13}$$

The return computed by each trader type for each asset is finally adjusted by a random variable uniformly distributed within its support, $\Theta_\gamma \in (-\theta_\gamma, \theta_\gamma)$, so that expectations are heterogeneous among the population of agents. Then, denoted as $\text{K} = \text{FUND,CHART,MACD,ROC,RSI}$, the expected return of each asset for the trader h at time t is

$$\mu_{h,t} = \frac{_{\text{K}}p_t^{exp} - p_t}{p_t} \pm \Theta_\gamma \tag{14}$$

2.1.2. Expected shortfall minimization

The Expected Shortfall (ES), also known as Conditional Value-at-Risk (CVaR), is a widely used risk measure that aims to capture the tail risk of a financial asset or a portfolio. The ES is built on VaR, but it offers a more comprehensive perspective. While VaR concentrates on the maximum loss within a certain threshold, the ES delves more deeply by considering the average of losses beyond the VaR threshold. This means that the ES takes into account the magnitude of losses and provides a more in-depth view of risk that extends beyond VaR.

To compute the ES, the first step is to calculate the VaR. There are different approaches to calculate the VaR among which are the historical simulation, Monte Carlo Analysis, and parametric approach. In this model, we used historical simulation estimating the VaR by computing the distribution of returns based on past observations. The method involves selecting a historical period and simulating the possible losses that would have occurred if the portfolio was held during that time. The ES is, then, estimated by taking the average of the worst losses that exceed the VaR. A limitation of this method is the assumption that the distribution of returns is stable over time and that, thus, their past behaviour is a reliable source of information for predicting their future dynamics. Mathematically:

$$\text{ES}_\alpha = \frac{1}{T}\sum_{i=1}^{N} r_i \times \mathbb{I}(r_i \leq \text{VaR}_\alpha) \tag{15}$$

where, ES_α represents the Expected Shortfall at confidence level α, T is the total number of historical returns, r_i stands for the ith historical return, VaR_α is the Value at Risk at confidence level α and $\mathbb{I}(r_i \leq \text{VaR}_\alpha)$ is an indicator function that equals 1 if r_i is less than or equal to VaR_α, and 0 otherwise. In this case, the heterogeneity of traders is represented by allowing each of ES-traders h to choose a personal value of α, i.e., $0.01 \leq \alpha_h \leq 0.1$.

Here, we introduce a simple routine to minimize the ES, based on a systematic assessment of possible different allocations for two assets in

Table 1
Parameters setting for the model with exogenous data.

Parameter	Name	Value	Parameter	Name	Value
H	NUMBER OF TRADERS	1995	n	NUMBER OF STOCKS	2
$m_{h,0}$	INITIAL AMOUNT OF MONEY	250	$q_{h,1,0} = q_{h,2,0}$	INITIAL AMOUNT OF STOCKS	0
$\theta_{\gamma=d}$	HETEROGENEITY	(−0.025, 0.025)	T_w	WINDOW LENGTH	30
$\theta_{\gamma=60}$	HETEROGENEITY	(−0.005, 0.005)	$\theta_{\gamma=5}$	HETEROGENEITY	(−0.002, 0.002)

the portfolio. Since we assume that the sum of weights for the assets, denoted as w_1 and w_2, always adds up to 1, the routine tries all possible weights combinations starting from $w_1 = 1$ and $w_2 = 0$ and at each iteration, decreases w_1 by 0.01 while increasing w_2 by 0.01. During each step, we compute the ES for the portfolio using the chosen pair of weights. The process continues until $w_1 = 0$ and $w_2 = 1$. Finally, the weight combination resulting in the lowest ES is selected as the optimal portfolio allocation.

2.1.3. Zero–intelligence trading

"Zero–intelligence" traders, also called "noise" traders, decide randomly the timing and the quantity of assets of their investments. Several studies have focused on the role of this kind of traders, especially to use them to represent the absence of influence and imitation, in order to challenge traditional views on financial dynamics and uncover new insights for reducing market volatility. In our model, random traders are the only ones not using technical strategies to optimize their portfolio and, instead, decide their investment (to buy or sell), at each time step, by "flipping a fair coin". The quantity of each asset to hold is determined by simply extracting w_1 as a random variable drawn, with uniform distribution, in $[0, 1]$ and consequently by computing $w_2 = 1 - w_1$, provided that the choice is restricted to pairs of weights compliant to the consistence of trader's wealth and stocks endowment.

2.2. The back-testing model

The model is constituted by agents creating portfolios by means of optimal weights, computed as shown above, according to the available data. In particular, we adopted financial time series of prices of real assets described in the following subsection. The disclosure of new data, for each time step, mimics the realism of agents living in the market and choosing as if transactions were happening actually in their time and they were experiencing prices for the first time. Operatively, this means that during the simulation, time series are disclosed to market participants time step by time step. In this case, we have to assume that simulated traders are marginal with respect to the whole market, in such a way that we can neglect the price impact of their orders.

2.2.1. Data

Our analysis has been conducted using price series with three different resolutions, $\gamma = d$, 60, 5, corresponding to daily, hourly and 5 min data. Table 1 shows the parameters of the back-testing agent-based model. All used time series have been downloaded by using Refinitiv's Eikon ©. Table 2 lists the assets used in the model. For each of them, the starting date for daily data is indicated in parentheses. Intraday series have been considered at their maximum available length: one year for hourly data and three months for 5-min data.

2.3. The order-book model

The model is built by considering a financial market with H heterogeneous agents, each endowed at $t = 0$ with an initial wealth $Y_{h,0} = \bar{Y}$, composed by money $m_{h,0}$ and two assets A_1 and A_2. We adopt two order-books operating simultaneously. Agents populating the model trade in both markets, making decisions about the quantities of both assets to hold in their optimal portfolios. All agents, without any coordination among them, start optimizing their portfolios by using one of the strategies described above. Thus, they choose the order configuration, i.e., the selection of prices and quantities. Once the order-book is populated by the submission of orders, transactions may occur.

2.3.1. Portfolio optimization

Each trader h tries to maximize her portfolio value, computed as $Y_{h,t} = m_{h,t} + p_{1,t}q_{h,1,t} + p_{2,t}q_{h,2,t}$, at any time t, being $m_{h,t}$ the quantity of her money, $p_{1,t}$ and $p_{2,t}$ the market prices of the two assets and $q_{h,1,t}$ and $q_{h,2,t}$ the quantities of the two assets in her endowment. The determination of optimal weights for both assets is the result of the first step of the model, and it is executed as previously explained. However, in the formation of expectations, in this case, two factors come into play: the potential role of imitation of other market participants and the impact of the market itself.

Our model considers the possibility that traders are interconnected, in a random network (Erdös, Rényi, et al., 1959), and exchange information regarding their expectations. Consequently, imitative processes may arise because of the spread of opinions via traders' connections. Simplifying the notation, and recalling that all agents form their expectations according to their trader type, as explained above, denoted as H_h the set of $j \equiv |H_h|$ neighbours of trader h, the expectation for the price of asset i, computed by h ($p^{exp}_{h,i,t}$) can be influenced, becoming

$$\tilde{p}^{exp}_{h,i,t} = (1 - \xi_h) p^{exp}_{h,i,t} + \xi_h\, p^{\text{NET}}_{h,i,t} + (1 + \iota_{h,t}) \Delta\pi_{t-1} \qquad i = 1, 2. \tag{16}$$

where, $p^{\text{NET}}_{h,i,t} = (1/j) \sum_{r}\, _j p^{exp}_{i,r \in H_{h,t}}$ is the average expectations of h's neighbours, $\xi_h \in (0, 1)$ is the sensibility of h to their opinions, and $(1 + \iota_{h,t})\Delta\pi_{t-1}$ will be introduced later.

2.3.2. Position

Once optimal weights have been calculated, the behaviour of each trader is easily identified by means of the comparison between the quantity of each asset that she had in her portfolio ($q_{h,i,t-1}$) and the newly determined optimal quantity ($q^*_{h,i,t}$). Thus, for each asset, traders compute the difference $\Delta q_{h,i,t} = q_{h,i,t-1} - q^*_{h,i,t}$ and her market position is:

$$\text{if } \Delta q_{h,i,t} > 0 \rightarrow \text{ask}, \qquad \text{if } \Delta q_{h,i,t} = 0 \rightarrow \text{hold}, \qquad \text{if } \Delta q_{h,i,t} < 0 \rightarrow \text{bid}$$

2.3.3. Orders setting

For each asset, all orders are posted to the corresponding order-book, which is a listing structure consisting of two sections: one for purchases, i.e., bid orders (arranged in descending order of price) and the other for sales, i.e., ask orders (arranged in ascending order of prices). The "best bid" ($_{\text{B}}p^{best}_{i,t}$) is defined as the price associated with the bid order having the highest price. Similarly, the "best ask" ($_{\text{A}}p^{best}_{i,t}$) is the price of the ask order with the lowest price.

Traders can place both limit and market orders, defined as in Chiarella et al. (2009), by comparing the price of the order and the best price on the other side of the order-book. In particular, $_{\text{B}}p_{h,i,t} \geq\, _{\text{A}}p^{best}_{i,t}$ and $_{\text{A}}p_{h,i,t} \leq\, _{\text{B}}p^{best}_{i,t}$ are, respectively, a bid and an ask market orders; $_{\text{B}}p_{h,i,t} <\, _{\text{A}}p^{best}_{i,t}$ and $_{\text{A}}p_{h,i,t} >\, _{\text{B}}p^{best}_{i,t}$ are bid/ask limit orders.

Pricing rules are symmetric and based on the willingness to pay/to accept of traders ($\omega_{h,t} \in (0, 1)$) and on the price differential, defined as $p^{\Delta}_{h,i,t} = p^{exp}_{h,i,t} - p_{i,t}$ where $p_{i,t}$ is the market price of asset i at the time t.

BID PRICING: ASK PRICING:

$$\begin{aligned} _{\text{B}}p^{\text{LMT}}_{h,i,t} &= p_{h,i,t} - (1 + \omega_{h,t}) p^{\Delta}_{h,i,t} & \qquad _{\text{A}}p^{\text{LMT}}_{h,i,t} &= p_{h,i,t} + (1 + \omega_{h,t}) p^{\Delta}_{h,i,t} \\ _{\text{B}}p^{\text{MKT}}_{h,i,t} &= p_{h,i,t} + (1 + \omega_{h,t}) p^{\Delta}_{h,i,t} & \qquad _{\text{A}}p^{\text{MKT}}_{h,i,t} &= p_{h,i,t} - (1 + \omega_{h,t}) p^{\Delta}_{h,i,t} \end{aligned} \tag{17}$$

The quantity of both assets depends on $\Delta q_{h,i,t}$. In the model, neither short selling nor loans are allowed.

Table 2
Time series used to perform simulations.

Asset name (since)	Asset name (since)	Asset name (since)
3M (02/01/73)	GENERAL ELECTRIC (02/01/73)	PFIZER (02/01/73)
ACCENTURE (19/07/01)	GENERAL MOTORS (18/11/10)	PHILIP MORRIS (17/03/08)
ADIDAS (17/11/95)	GOODYEAR (02/01/73)	PHILIPS (01/01/73)
ADOBE SYSTEMS (24/11/86)	HEINEKEN (01/01/73)	SAMSUNG (02/07/84)
ALPHABET (19/08/04)	HENKEL (02/07/96)	ROYAL DUTCH SHELL (01/01/73)
AMERICAN EXPRESS (02/01/73)	HEWLETT-PACKARD (02/01/73)	SIEMENS (01/01/73)
APPLE (12/12/80)	INTEL (02/01/73)	SONY (01/01/73)
AT&T (21/11/83)	INTESA SAN-PAOLO (01/01/73)	TELEFONICA (02/03/87)
BARCLAYS (30/12/64)	JOHNSON&JOHNSON (02/01/73)	TESLA (29/06/10)
BMW (01/01/73)	JPMORGAN (02/01/73)	TEXAS INSTRUMENTS (02/01/73)
CISCO (16/02/90)	ESSILORLUXOTTICA (28/10/75)	THOMSON REUTERS (12/06/02)
COLGATE/PALMOLIVE (02/01/73)	MICROSOFT (13/03/86)	NETFLIX (23/05/02)
DAIMLER (26/10/98)	DEERE&COMPANY (02/01/73)	TOTAL (01/01/73)
DANONE (01/01/73)	MORGAN/STANLEY (23/02/93)	VOLKSWAGEN (01/01/73)
DEUTSCHE TELEKOM (15/11/96)	NESTLÉ (01/01/73)	WALT DISNEY (02/01/73)
EXXON (02/01/73)	ORACLE (12/03/86)	AMAZON (15/05/97)
FORD MOTOR (02/01/73)	STARBUCKS (26/06/92)	

Table 3
Parameters setting for the model with the order-book and endogenous data.

Parameter	Name	Value	Parameter	Name	Value
$m_{h,0}$	INITIAL AMOUNT OF MONEY	50 000	$q_{h,1,0} = q_{h,2,0}$	INITIAL AMOUNT OF STOCK	250
τ_j	TRADERS' TIME WINDOW	30	λ_{ob}	ORDER-BOOK LENGTH	3
$w_{h,t}$	AGENTS'S WTA/ WTP	$\in [0, 1]$	ξ_h	SENSIBILITY TO OPINIONS	$\in [0, 1]$

2.3.4. Order-book setting

Limit orders are only effective for a specified period of time, and they will be executed if the market price crosses them during it. If not, once their validity period expires, they are cancelled from the order-book. However, as in Lux and Marchesi (1999, 2000), we assume that these orders persist in the market, representing the market sentiment, as an expression of the excess demand or excess supply. During each time step t, traders perceive this "pressure", determined as the ratio between the count of pending ask (${}_{A}n_{t-1}$) and bid (${}_{B}n_{t-1}$) limit orders, in $t-1$.

$$\Delta\pi_{t-1} = \begin{cases} ({}_{A}n_{t-1}/{}_{B}n_{t-1}) & \text{if} \quad {}_{A}n_{t-1} > {}_{B}n_{t-1} \\ 0 & \text{if} \quad {}_{A}n_{t-1} = {}_{B}n_{t-1} \\ ({}_{B}n_{t-1}/{}_{A}n_{t-1}) & \text{if} \quad {}_{A}n_{t-1} < {}_{B}n_{t-1} \end{cases} \tag{18}$$

As shown in Eqs. (16), the impact of this market sentiment depends on $(1 + \iota_{h,t})$ (with $\iota_{h,t} \in [0.1, 1]$), i.e. the degree of knowledge about the order-book listing queue.

When a market order is placed, it is executed immediately at the best available price on the opposite side of the order-book. If $q_t^{B} = q_t^{A}$, the transaction is executed. If, instead, $q_t^{B} \neq q_t^{A}$, the volume of trade will be the "shortest side of the market", i.e., the order with the smallest quantity, which will be removed from the order-book once executed. The trader whose order has not been fully satisfied remains in the order-book, for the residual quantity, waiting for a new match. This procedure continues until either the unmatched quantity is completely satisfied or the maximum order-book length (λ_{ob}) is reached, being λ_{ob} the number of counterparts an order can match within a single round of transactions.

2.3.5. Transactions

Transactions execute orders, implying the update of portfolios of participating traders and of the market price. After transactions of a time step t are negotiated, the entire process is repeated for the time step $t+1$.

At each time t the same sequence of phases is repeated. Parameters regulating the order-book are shown in Table 3.

3. Results

In this section we present results obtained from both the back-testing and the order-book models presented above.

3.1. Back-testing simulation with exogenous prices

As above explained, the aim of this paper is to compare three different portfolio optimization strategies: the minimization of the Expected Shortfall (ES), the maximization of the Sharpe ratio (S) -computed by adopting five different behavioural rules to model expectations according to acknowledged approaches of technical analysis, and a completely random portfolio selection. In order to simplify the presentation of results, we will thus refer to $z = 7$ different strategies, and consider the Sharpe ratio maximization strategy split into five different ones, each corresponding to the technique used by traders to compute their expectations. At the initial setup, each trader is assigned one of the strategies, in such a way that they are equally distributed among all agents. Thus, presented results referred to each strategy are averaged over all traders adopting it.

A first results is oriented to assess the performance of each strategy: according to the simulated portfolio values at the end of the trading period, we obtain a ranking of strategies and compute the number of times that a given strategy is placed at a certain position ζ_z, with $z = 1, 2, \ldots, 7$. Fig. 1 compares the number of times each strategy placed in the first (ζ_1) and the last (ζ_7) position over the 1225 rankings analysed, for all considered data resolutions.

Results indicate that there is not a technical strategy that has clearly outperformed the others. With regards to daily data, some strategies have been in both the top and bottom positions multiple times. For instance, ROC led 287 times and failed 280 times. Other strategies, such as RSI, MACD–Divergence and fundamentalists, showed not very good performances, scoring best fewer times than worst. The chartist strategy and the random one displayed the most remarkable results, scoring first 250 and 245 times and last only 109 and 58 times, respectively. In contrast, ES traders had the least impressive performance, reaching the top of the ranking only 11 times and the bottom 149 times.

The resolution of adopted data seems to have a role in influencing the performance of different strategies: RSI, ROC, MACD–Divergence and, once again, "zero–intelligence", performed well with hourly data, experiencing fewer failures and more occurrences of arriving in the first position. Passing from less to more resolution, chartists showed a decline in performance. Fundamentalists and, again, ES strategy performed poorly, being the best only occasionally (less than 100 times) and arriving last significantly more often than they arrive first (the difference between the best and worse results is 241 and 224, respectively).

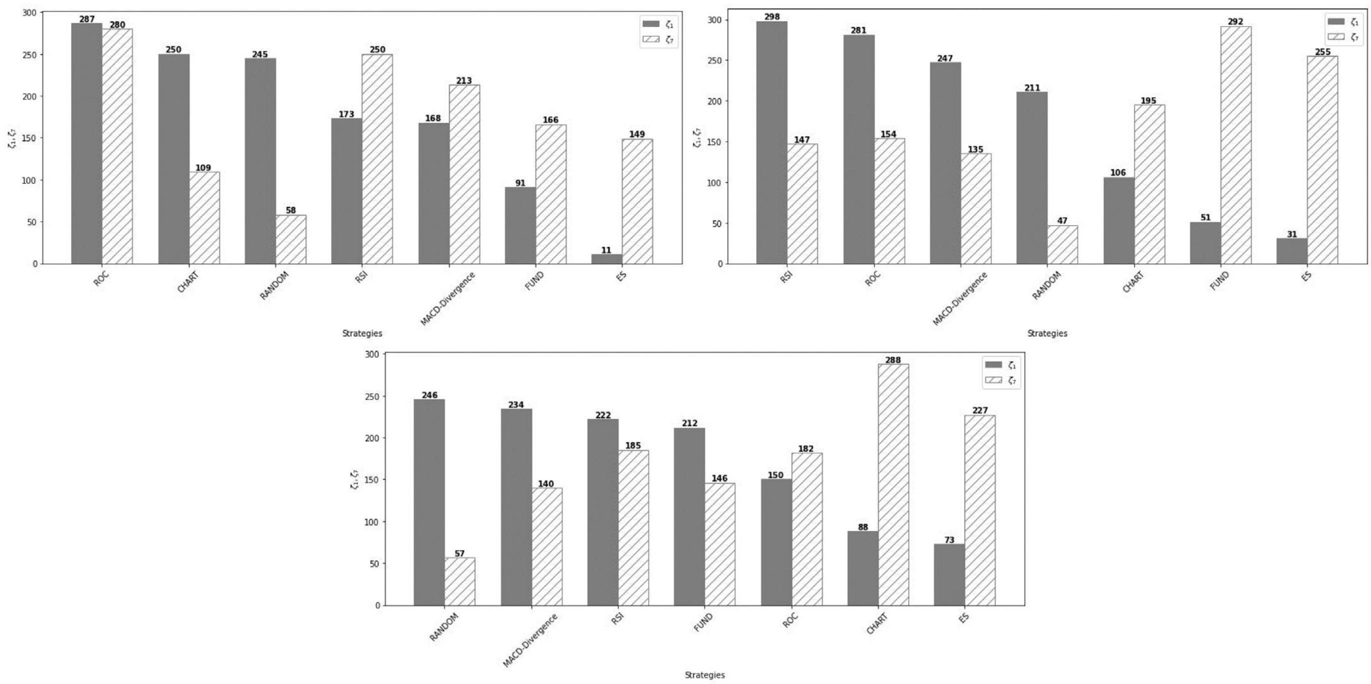

Fig. 1. Occurrences for strategies in the first/last position for portfolio values. Top: daily (left), hourly (right); Bottom: 5-min results.

Table 4
Performance ranking of strategies with exogenous price.

Strategy	Daily data				Hourly data				5-min data				Ranking
	$\zeta_{\leq 3}$	$\zeta_{\geq 5}$	η	η_{norm}	$\zeta_{\leq 3}$	$\zeta_{\geq 5}$	η	η_{norm}	$\zeta_{\leq 3}$	$\zeta_{\geq 5}$	η	η_{norm}	$\bar{\eta}_{norm}$
RND	733	317	2,31	1,00	737	292	2,52	1,00	712	304	2,34	1,00	1,00
MACD	499	566	0,88	0,22	640	416	1,54	0,55	629	425	1,48	0,54	0,44
ROC	578	549	1,05	0,31	659	411	1,60	0,58	502	537	0,93	0,26	0,38
RSI	496	595	0,83	0,19	686	416	1,65	0,60	552	512	1,08	0,33	0,38
CHART	645	418	1,54	0,58	444	584	0,76	0,20	366	701	0,52	0,04	0,27
FUND	416	589	0,71	0,12	264	774	0,34	0,01	586	474	1,24	0,41	0,18
ES	308	641	0,48	0,00	245	782	0,31	0,00	328	722	0,45	0,00	0,00

Notably, with 5-min data, chartists' performance continues to decline, being last 288 times and first only 88. Compared to the hourly data rate, ROC traders also worsen their performance, having for the first time a negative gap between first and last place in the ranking. Conversely, fundamentalists significantly improved their performance, ranking, for the first time, more frequently in the best position (212) than in the last one (146).

The random strategy exhibits very good performances across all data resolutions, as shown by results presented in Table 4 where, for each strategy, the cumulative occurrences of ranking in the top three ($\zeta_{\leq 3}$) and in the last three ($\zeta_{\geq 5}$) positions have been reported, along with the ratio between the two values, ($\eta = \frac{\zeta_{\leq 3}}{\zeta_{\geq 5}}$), normalized in $[0, 1]$, as:

$$\eta_{norm} = \frac{\eta - min_\eta}{max_\eta - min_\eta} \tag{19}$$

being min_η and max_η, respectively, the minimum and the maximum value of the ratio. The final ranking has been computed by averaging the normalized ratios obtained for each data resolution ($\bar{\eta}_{norm}$).

Results show that in the simulations with exogenous data, the random strategy is, on average, the best performing strategy, reaching the top three positions significantly more often than the last three. The worst performer was, instead, the ES strategy, consistently ranking among the last three strategies. Among the technical strategies used to compute expectations in the Sharpe ratio maximization, the MACD–Divergence technique emerged as the best one.

We have also investigated the temporal evolution of the wealth of traders for each strategy. Figs. 2–4 show the average of 1125 simulations using all possible pairs of assets for daily, hourly, and 5-min data, respectively.

Overall, results for wealth align with the observed rankings. With daily data, results show that during the first 90 days of trading, fundamentalists performed strongly. However, over time, their performance decreases, probably due to the increment of volatility –common to many time series– with respect to their initial values and is outperformed by the ROC strategy, maintaining the highest level of wealth for over 15 years of trading. Nevertheless, in the final stages of the simulation, ROC traders experienced numerous failures, indicating the risky nature of their approach. In contrast, over the long term, chartists demonstrated resilience and emerged as the top-performing group at the end of the period.

Analysing hourly data, all strategies initially fall below the starting wealth within the first few days of trading. However, they gradually recovered, with RSI, ROC and MACD strategies consistently demonstrating the most promising bounce-back. Within the first 30 days all strategies steadily increased. After three months of trading, RSI, stood out as the most successful strategy, while ES traders and fundamentalists proved to be the worst performers.

Moving to the case with 5 minutes data, in the very short term (one day), all strategies faced wealth losses. Traders following the ES strategy incurred in the lowest drawdowns. As the analysis extends to a medium-term period of one week, strategies started to recover, and profits began to appear for most of them, with fundamentalists

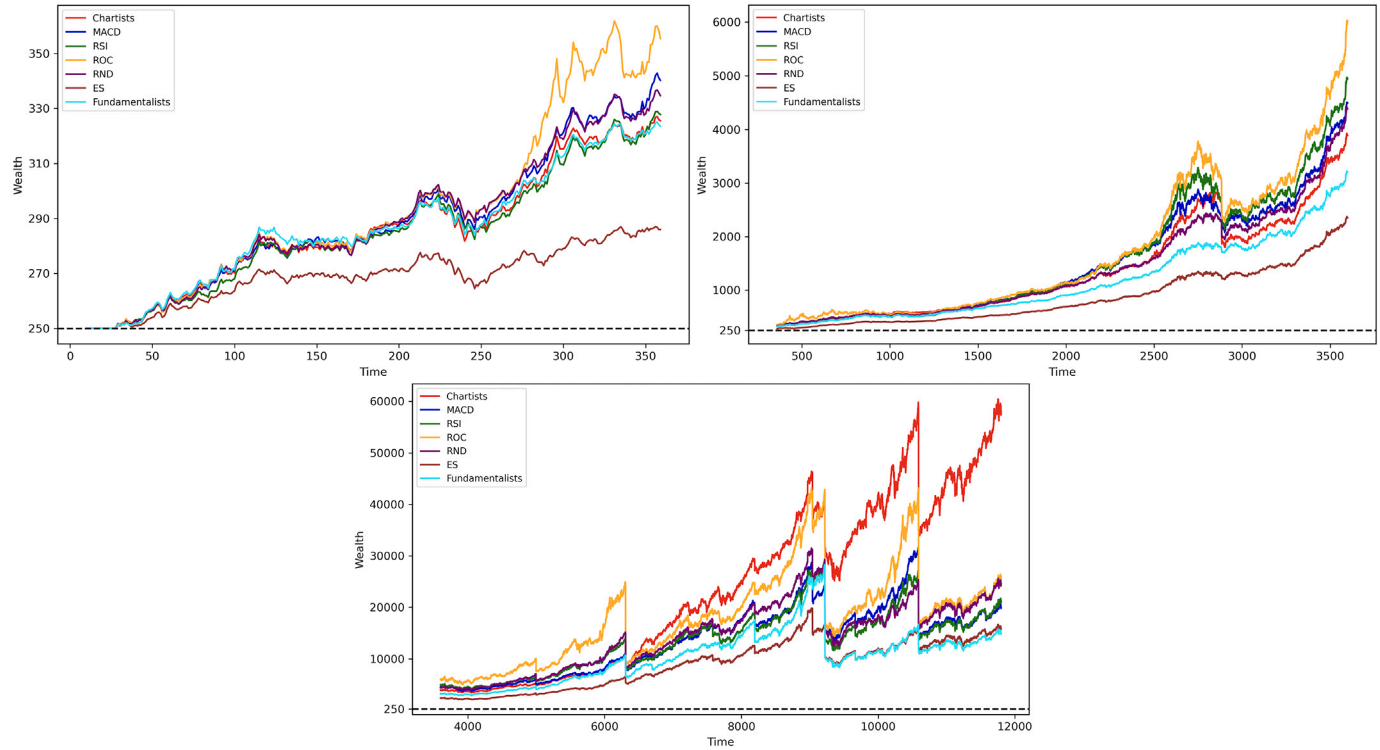

Fig. 2. Evolution of wealth with daily data: first year of trading (top-left), second to tenth year (top-right) and final period (bottom).

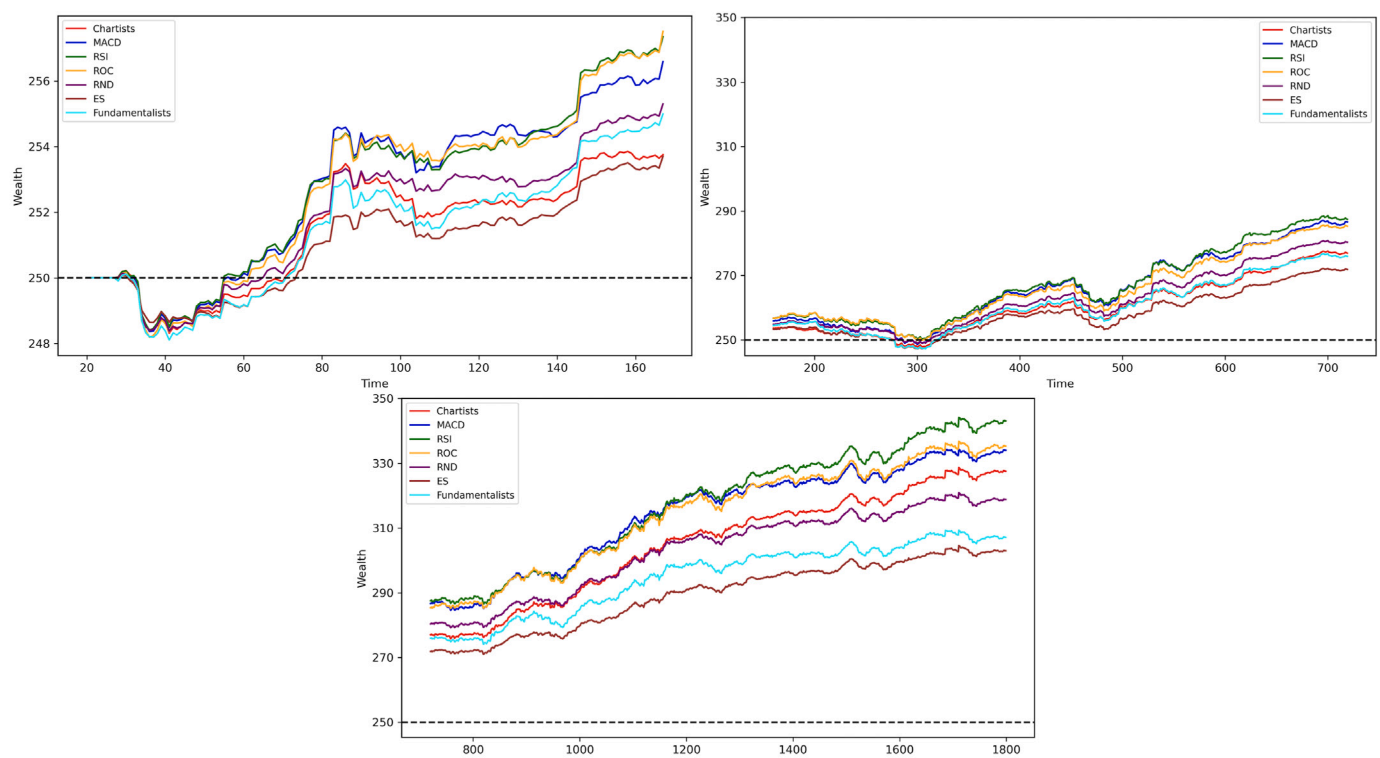

Fig. 3. Evolution of wealth with hourly data: first week of trading (top-left), first month (top-right) and final period (bottom).

presenting the strongest performance. In contrast, chartists consistently lagged behind, struggling to achieve positive returns. Ultimately, at the end of the period, the MACD strategy was the most successful in generating profits.

3.2. *The order-book simulation with endogenous prices*

In this second framework, prices directly emerge from the simulated transactions among traders. Step by step, they compute the weights of

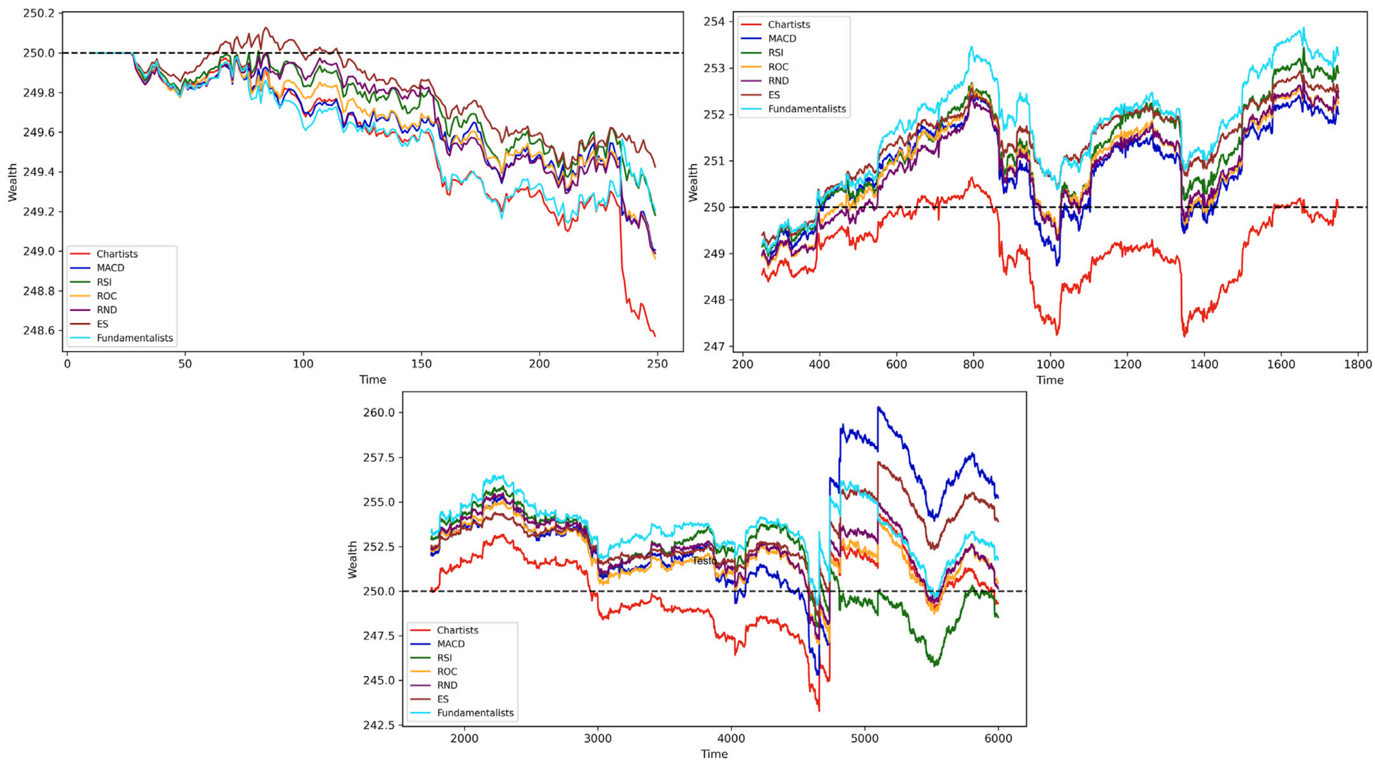

Fig. 4. Evolution of wealth with 5-min data: first day of trading (top-left), first week (top-right) and final period (bottom).

the two assets needed to maintain an optimal portfolio at all times. Based on these weights, they place bid or ask orders in both of the order-books presented in the markets. The two order-books operate in the same way. Compared to the previous scenario, in this case, agents may not always find counterparts for their desired trades, which means they might not always obtain the exact quantity of assets they want.

Firstly, we tested the ability of the model to replicate the stylized facts of the financial returns, i.e, the presence of fat tails of the probability density functions of returns (Gopikrishnan et al., 1999; Mandelbrot, 1963), the absence of autocorrelation (Cont et al., 1997; Pagan, 1996) and the presence of volatility clustering (Mandelbrot, 1963). The graphical analysis conducted in Fig. 5 shows that our model is able to replicate these facts quite effectively. The PDF of returns, the Autocorrelation Functions (ACF) of returns, and the ACF of absolute returns for four financial real-time series (APPLE, BMW, GENERAL ELECTRIC and PFIZER) have been compared with those of our simulated returns.

Subsequently, as in other studies such as Samarakoon and Hasan (2005) and Čuljak, Tomić, and Žiković (2022), we conducted a comparative analysis of portfolio performance. Various scenarios have been modelled, in which fundamentalists are always combined with one of the other strategies, the effects of which we want to examine on market dynamics. Portfolios were constructed with the equal allocation of the two assets.

Table 5 shows, for each scenario, the annualized returns and standard deviations, the Sharpe ratio (Sharpe, 1966), the Sortino ratio (Sortino & Price, 1994), the Treynor ratio (Treynor, 1965), the Modigliani and Modigliani measure ($M2$) (Modigliani & Modigliani, 1997), the Worst Drawdown, the Information ratio (Goodwin, 1998) and the Jensen's Alpha (Jensen, 1968). In order to compute such indices, a benchmark has been defined by utilizing an equally weighted portfolio, as in The S&P U.S. Indices (Dow Jones S&P, 2023), considering all strategies simultaneously.

Results shows that traders in Case 1 achieved the lowest annualized standard deviation and the worst drawdown, highlighting the ability of chartists to minimize losses. Although they had lower annualized returns compared to ES and random traders, the portfolio still performed well in terms of risk-adjusted measures, emphasizing the effective trade-off between returns and risk. Case 2, presents the impact of MACD strategy and shows that it did not excel in any of the metrics but managed to avoid being the worst performer. Case 3 and Case 4 displayed the weakest results, achieving the poorest values across various risk-adjusted measures such as the Sharpe, Sortino and Information ratios and the $M2$ measure. Additionally, in the scenario with ROC traders, we found the lowest annualized return. They also exhibited negative values for the Treynor ratio, indicating performance worse than that of a risk-free instrument. In Case 5, random traders achieved the highest Sharpe and Sortino ratios and $M2$ measure. However, they also had one of the worst drawdown, at 52%. Lastly, the portfolio in the Case 6 had the highest annualized return, indicating its potential to generate stronger returns. Despite this, its weaknesses in terms of having the worst drawdown and the highest annualized standard deviation suggest the need to increase stability.

Considering the outcomes from these indices, we further examined the performance level of various strategies by analysing cumulative returns and portfolio volatility over time, in Fig. 6.

Once again, the excellent performance of the strategy minimizing ES is evident in terms of cumulative returns. However, this portfolio also exhibits the highest volatility, as highlighted by the indices. Notably, as pointed out earlier, random traders demonstrate good cumulative returns and low volatility. Chartist strategy, which had previously performed well in terms of indices, also yields positive but not exceptionally high cumulative returns with moderate volatility. The remaining strategies show relatively low returns and average volatility. This evidence readdress the debate about the choice between more-volatile-more-remunerative assets and less-volatile-less-remunerative ones: ourfindings seem to prove that costly strategies are

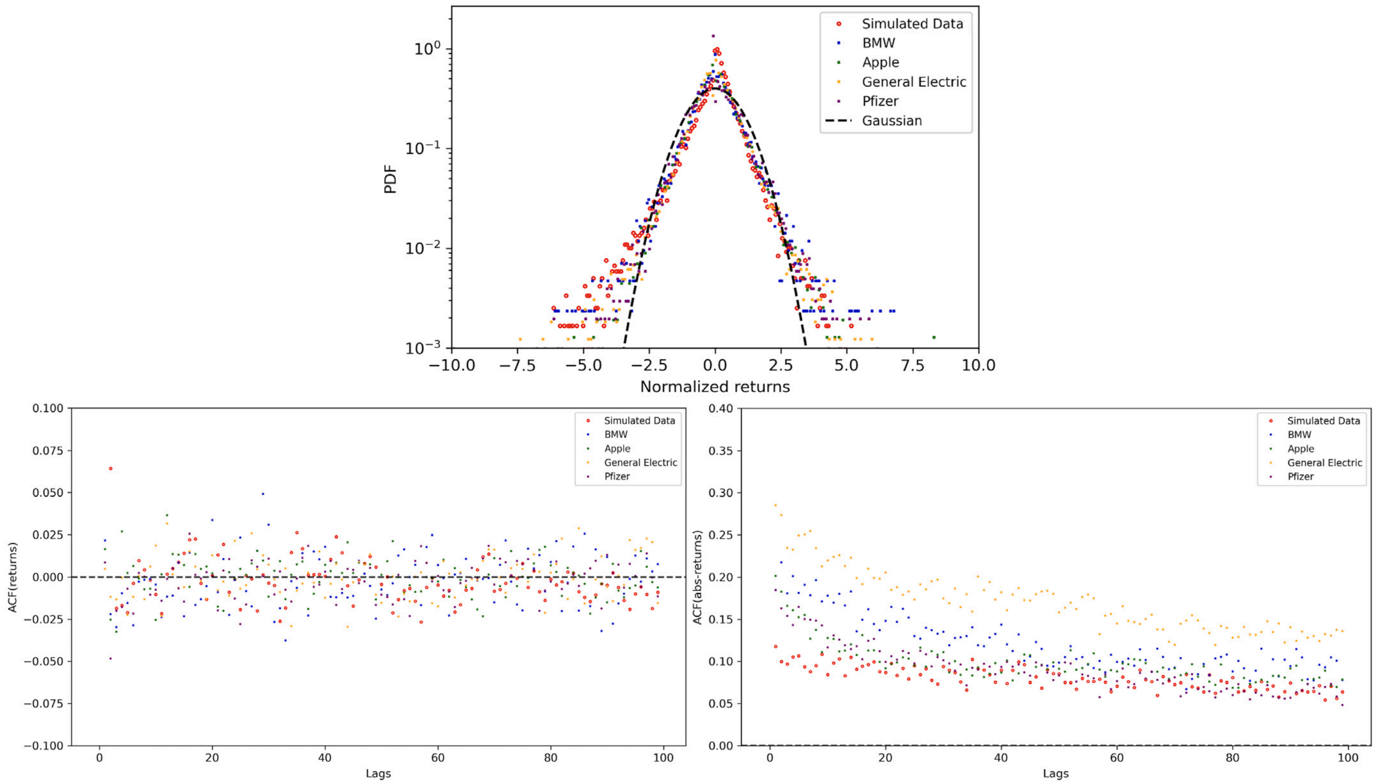

Fig. 5. Density functions (top), ACF (bottom-left) of empirical returns and ACF of absolute returns (bottom-right) of four financial real time series compared with the one of simulated returns of the first asset.

Table 5
Performance Indices. Columns indicate, in order, results for: Annualized returns, Annualized Standard Deviation, Sharpe ratio, Sortino ratio, Treynor ratio, $M2$ Measure, Worst Drawdown, Information ratio and Jensen's Alpha.

#Case	Traders	μ_a	σ_a	SR	STR	TR	M2	WD	IR	α_J
Benchmark		0.001842	0.125560	0.232928	0.321447	0.001842	0.029248	−0.612970	//	//
1	F + Chart	0.002188	0.086809	0.387067	0.52807	1.188554	0.048602	−0.37125	0.028901	0.00013
2	F +MACD	0.002152	0.151787	0.225110	0.280481	0.144176	0.028279	−0.53182	−0.01509	0.00013
3	F +RSI	0.001692	0.129174	0.250421	0.308051	//	0.031444	−0.48619	0.017523	0.00013
4	F +ROC	0.001175	0.107557	0.193459	0.249972	//	0.024292	−0.51615	−0.05055	0.00008
5	F +RND	0.002797	0.102735	0.432233	0.594295	0.986035	0.054177	−0.52364	0.015884	0.00018
6	F +ES	0.006267	0.251509	0.395567	0.48405	//	0.049279	−0.68895	0.199506	0.00039

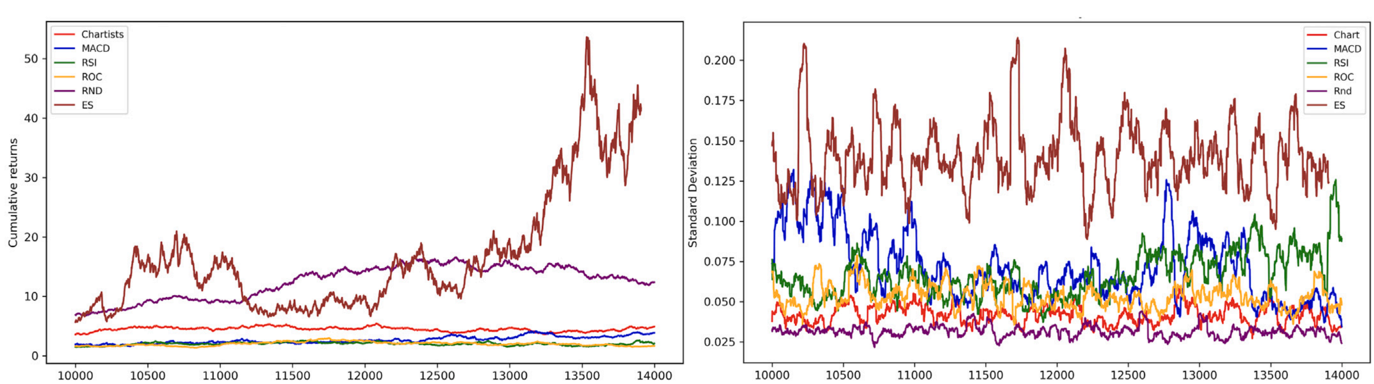

Fig. 6. Cumulative returns (left) and volatility of strategies (right) in time for simulated data.

not able to outperform a very easy, cheap but effective strategy based on chance. Further, the individual result emerging from our simulations is not the only conclusion worth to be noted. Indeed, a more stable market, where the financial transactions are not guided by imitation and volatility, is a prerequisite for a sound economic development.

4. Concluding remarks

This paper presented a comparison between three financial portfolio optimization methods: maximizing the Sharpe ratio, with five distinct strategies for the expectations computation; minimizing the Expected

Shortfall and employing a "zero–intelligence" trading approach. An agent-based model was introduced to simulate heterogeneous traders aiming to achieve the highest portfolio values. Initially, portfolios with two assets were built using all possible combinations of 50 real series, using both daily and intraday data. Subsequently, an innovative model incorporating two truly operating order-books was developed to examine results with endogenous prices. A key feature of this model is agents' ability to operate simultaneously in both markets, enabling them to buy or sell both assets.

Although analysis has revealed that there is no superior strategy among all others, two key results are evident. Our initial finding, which is consistent with previous research (as in Biondo, Pluchino, Rapisarda, and Helbing (2013b)), highlights the good performance of the "zero–intelligence" approach. For individual traders, this means they have a free option that performs similarly or even better than technical strategies requiring expensive professional financial advice.

Another evident result is that strategies that have generally performed well in terms of high returns, such as ES-minimizing, are characterized by higher volatility. On the other hand, other strategies, like the one followed by chartists, show lower overall volatility and risk while generating modest but positive returns. This may be particularly appealing to investors favouring a more conservative approach or prioritizing prudent risk management in their investments.

In conclusion, we face a choice between two paths. On one hand, there is the tempting option of aiming to higher profits, but this comes at the cost of dealing with uncertainty and potential losses due to market volatility. On the other hand, opting for positive but smaller gains per transaction offers a more stable investment journey. Considering that the financial system is unpredictable being a complex system and that we cannot know when these gains and losses will happen, focusing on stability and, thus, adopting the second approach, may be a more effective strategy.

Therefore, individual and social goals should be aligned. Although to some risk-loving traders the illusory temptation of higher-profit investments may appear appealing, gains from riskier transactions are merely the result of fortunate short-term operations, and not accurate predictions. In contrast, the lack of significant profits from more secure investments is balanced by a reduction of aggregate volatility. This increased stability proves to be successful, both from a macro perspective and for single traders, as they can achieve similar returns through more frequent, less profitable investments.

CRediT authorship contribution statement

Alessio Emanuele Biondo: Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Laura Mazzarino:** Data curation, Investigation, Methodology, Resources, Software, Validation, Visualization; Writing – original draft, Writing – review & editing. **Alessandro Pluchino:** Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Data availability

No.

Acknowledgment

A.E.B. and A.P. acknowledge the support by Ministero dell'Istruzione, dell'Università e della Ricerca - MIUR, project PRIN 2017WZFTZP "Stochastic forecasting in complex systems".

References

Alfarano, S., & Lux, T. (2007). A noise trader model as a generator of apparent financial power laws and long memory. *Macroeconomic Dynamics*, *11*(S1), 80–101.

Alfarano, S., Lux, T., & Wagner, F. (2005). Estimation of agent-based models: the case of an asymmetric herding model. *Computational Economics*, *26*, 19–49.

Artzner, P., Delbaen, F., Eber, J., & Heath, D. (1997). Thinking coherently. risk, 10. *November*, *68*, 71.

Artzner, P., Delbaen, F., Eber, J.-M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, *9*(3), 203–228.

Axtell, R. L., & Farmer, J. D. (2022). Agent-based modeling in economics and finance: Past, present, and future. *Journal of Economic Literature*.

Bak, P., Paczuski, M., & Shubik, M. (1997). Price variations in a stock market with many agents. *Physica A. Statistical Mechanics and its Applications*, *246*(3–4), 430–453.

Ban, G.-Y., El Karoui, N., & Lim, A. E. (2018). Machine learning and portfolio optimization. *Management Science*, *64*(3), 1136–1154.

Beja, A., & Goldman, M. B. (1980). On the dynamic behavior of prices in disequilibrium. *The Journal of Finance*, *35*(2), 235–248.

Benati, S., & Rizzi, R. (2007). A mixed integer linear programming formulation of the optimal mean/value-at-risk portfolio problem. *European Journal of Operational Research*, *176*(1), 423–434.

Biondo, A. E. (2018). *Studies in economics and finance*, *Order book microstructure and policies for financial stability*. Emerald Publishing Limited.

Biondo, A. E., Mazzarino, L., & Rossello, D. (2021). Portfolio optimization and trading strategies: a simulation approach. In *CEUR workshop proceedings*.

Biondo, A. E., Pluchino, A., & Rapisarda, A. (2013a). The beneficial role of random strategies in social and financial systems. *Journal of Statistical Physics*, *151*, 607–622.

Biondo, A. E., Pluchino, A., Rapisarda, A., & Helbing, D. (2013b). Are random trading strategies more successful than technical ones? *PLoS One*, *8*(7), Article e68344.

Black, F., & Litterman, R. (1991). Global portfolio optimization. *Journal of Fixed Income*, (1).

Black, F., & Litterman, R. (1992). Global portfolio optimization. *Financial Analysts Journal*.

Boutouria, N., Hamad, S. B., & Medhioub, I. (2020). Investor behaviour heterogeneity in the options market: Chartists vs. fundamentalists in the French market. *Journal of Economics and Business*, *3*(2).

Brock, W. A., & Hommes, C. H. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control*, *22*(8–9), 1235–1274.

Brown, D. B., & Smith, J. E. (2011). Dynamic portfolio optimization with transaction costs: Heuristics and dual bounds. *Management Science*, *57*(10), 1752–1770.

Campbell, R., Huisman, R., & Koedijk, K. (2001). Optimal portfolio selection in a Value-at-Risk framework. *Journal of Banking & Finance*, *25*(9), 1789–1804.

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., & Whitelaw, R. F. (1998). The econometrics of financial markets. *Macroeconomic Dynamics*, *2*(4), 559–562.

Chakraborti, A., Toke, I. M., Patriarca, M., & Abergel, F. (2011). Econophysics review: I. Empirical facts. *Quantitative Finance*, *11*(7), 991–1012.

Chen, A. H., Fabozzi, F. J., & Huang, D. (2010). Models for portfolio revision with transaction costs in the mean–variance framework. In *Handbook of portfolio construction* (pp. 133–151). Springer.

Chiang, Y.-C., Ke, M.-C., Liao, T. L., & Wang, C.-D. (2012). Are technical trading strategies still profitable? Evidence from the Taiwan stock index futures market. *Applied Financial Economics*, *22*(12), 955–965.

Chiarella, C. (1992). The dynamics of speculative behaviour. *Annals of Operations Research*, *37*(1), 101–123.

Chiarella, C., Dieci, R., & He, X.-Z. (2007). Heterogeneous expectations and speculative behavior in a dynamic multi-asset framework. *Journal of Economic Behavior and Organization*, *62*(3), 408–427.

Chiarella, C., & Iori, G. (2002). A simulation analysis of the microstructure of double auction markets. *Quantitative finance*, *2*(5), 346.

Chiarella, C., Iori, G., & Perelló, J. (2009). The impact of heterogeneous trading rules on the limit order book and order flows. *Journal of Economic Dynamics & Control*, *33*(3), 525–537.

Chopra, V., & Ziemba, W. (1993). The effect of errors in means, variances, and covariances on optimal portfolio choice. *The Journal of Portfolio Management*, *19*(2), 6–11.

Cincotti, S., Focardi, S. M., Marchesi, M., & Raberto, M. (2003). Who wins? Study of long-run trader survival in an artificial stock market. *Physica A. Statistical Mechanics and its Applications*, *324*(1–2), 227–233.

Consiglio, A., Lacagnina, V., & Russino, A. (2005). A simulation analysis of the microstructure of an order driven financial market with multiple securities and portfolio choices. *Quantitative Finance*, *5*(1), 71–87.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, *1*(2), 223.

Cont, R., & Bouchaud, J.-P. (2000). Herd behavior and aggregate fluctuations in financial markets. *Macroeconomic Dynamics*, *4*(2), 170–196.

Cont, R., Potters, M., & Bouchaud, J.-P. (1997). Scaling in stock market data: stable laws and beyond. In *Scale invariance and beyond* (pp. 75–85). Springer.

Cornuejols, G., & Tütüncü, R. (2007). *Optimization methods in finance*. Cambridge University Press.

Čuljak, M., Tomić, B., & Žiković, S. (2022). Benefits of sectoral cryptocurrency portfolio optimization. *Research in International Business and Finance*, *60*, Article 101615.

Day, R. H., & Huang, W. (1990). Bulls, bears and market sheep. *Journal of Economic Behavior and Organization*, *14*(3), 299–329.

Dieci, R., & He, X.-Z. (2018). Heterogeneous agent models in finance. In *Handbook of computational economics*: *vol. 4*, (pp. 257–328). Elsevier.

Dow Jones S&P (2023). Index mathematics methodology.

Erdös, P., Rényi, A., et al. (1959). On random graphs. *Publicationes mathematicae*, *6*(26), 290–297.

Feldman, T. (2010). Portfolio manager behavior and global financial crises. *Journal of Economic Behavior and Organization*, *75*(2), 192–202.

Fernández, A., & Gómez, S. (2007). Portfolio selection using neural networks. *Computers & Operations Research*, *34*(4), 1177–1191.

Frankel, J. A., & Froot, K. A. (1990). Chartists, fundamentalists, and trading in the foreign exchange market. *The American Economic Review*, *80*(2), 181–185.

Freitas, F. D., De Souza, A. F., & De Almeida, A. R. (2009). Prediction-based portfolio optimization model using neural networks. *Neurocomputing*, *72*(10–12), 2155–2170.

Gaivoronski, A. A., & Pflug, G. (2005). Value-at-risk in portfolio optimization: properties and computational approach. *Journal of Risk*, *7*(2), 1–31.

Golmakani, H. R., & Alishah, E. J. (2008). Portfolio selection using an artificial immune system. In *2008 IEEE international conference on information reuse and integration* (pp. 28–33). IEEE.

Goodwin, T. H. (1998). The information ratio. *Financial Analysts Journal*, *54*(4), 34–43.

Gopikrishnan, P., Plerou, V., Amaral, L. A. N., Meyer, M., & Stanley, H. E. (1999). Scaling of the distribution of fluctuations of financial market indices. *Physical Review E*, *60*(5), 5305.

Hommes, C. H. (2006). Heterogeneous agent models in economics and finance. In *Handbook of computational economics*: *vol. 2*, (pp. 1109–1186). Elsevier.

Hung, N. H. (2016). Various moving average convergence divergence trading strategies: A comparison. *Investment Management and Financial Innovations*, (13, Iss. 2 (contin. 2)), 363–369.

Idzorek, T. (2007). A step-by-step guide to the black-litterman model: Incorporating user-specified confidence levels. In *Forecasting expected returns in the financial markets* (pp. 17–38). Elsevier.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389–416.

Krokhmal, P., Palmquist, J., & Uryasev, S. (2002). Portfolio optimization with conditional value-at-risk objective and constraints. *Journal of Risk*, *4*, 43–68.

LeBaron, B. (2006). Agent-based computational finance. In *Handbook of computational economics*: *vol. 2*, (pp. 1187–1233). Elsevier.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, *47*, 13–37.

Lux, T., & Alfarano, S. (2016). Financial power laws: Empirical evidence, models, and mechanisms. *Chaos, Solitons & Fractals*, *88*, 3–18.

Lux, T., & Marchesi, M. (1999). Scaling and criticality in a stochastic multi-agent model of a financial market. *Nature*, *397*(6719), 498–500.

Lux, T., & Marchesi, M. (2000). Volatility clustering in financial markets: a microsimulation of interacting agents. *International Journal of Theoretical and Applied Finance*, *4*(3), 675–702.

Mandelbrot, B. B. (1963). The variation of certain speculative prices. *Journal of Business*, *36*(4), 394–419.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*, 77–91.

Maslov, S. (2000). Simple model of a limit order-driven market. *Physica A. Statistical Mechanics and its Applications*, *278*(3–4), 571–578.

Meucci, A. (2006). Beyond black-litterman in practice: A five-step recipe to input views on non- normal markets. Working paper.

Modigliani, F., & Modigliani, L. (1997). Risk-adjusted performance. *Journal of Portfolio Management*, *23*(2), 45–54.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica*, *34*, 768–783.

Murphy, J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. New York Institute of Finance.

Orito, Y., Kambayashi, Y., Tsujimura, Y., & Yamamoto, H. (2011). An agent-based model for portfolio optimization using search space splitting. In *Multi-agent applications with evolutionary computation and biologically inspired technologies: Intelligent techniques for ubiquity and optimization* (pp. 19–34). IGI Global.

Pagan, A. (1996). The econometrics of financial markets. *Journal of Empirical Finance*, *3*(1), 15–102.

Pätäri, E., & Vilska, M. (2014). Performance of moving average trading strategies over varying stock market conditions: the Finnish evidence. *Applied Economics*, *46*(24), 2851–2872.

Pflug, G. C. (2000). Some remarks on the value-at-risk and the conditional value-at-risk. In *Probabilistic constrained optimization: Methodology and applications* (pp. 272–281). Springer.

Ponta, L., Raberto, M., & Cincotti, S. (2011). A multi-assets artificial stock market with zero-intelligence traders. *Europhysics Letters*, *93*(2), 28002.

Rockafellar, R. T., Uryasev, S., et al. (2000). Optimization of conditional value-at-risk. *Journal of Risk*, *2*, 21–42.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica: Journal of the Econometric Society*, 431–449.

Ruppert, D. (2004). *Statistics and finance: An introduction*. Springer.

Samarakoon, L. P., & Hasan, T. (2005). Portfolio performance evaluation. In C. Lee (Ed.), *The encyclopedia of finance* (pp. 617–622). Springer.

Satchell, & Scowcroft (2000). A demystification of the Black-Litterman model: Managing quantitative and traditional portfolio construction. *The Journal of Asset Management*.

Sharpe, W. (1964). Capital asset prices: a theory of market equilibrium under condition of risk. *Journal of Finance*, *19*.

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, *39*(1), 119–138.

Sharpe, W. F. (1994). The sharpe ratio. *Journal of Portfolio Management*, *21*(1), 49–58.

Sortino, F. A., & Price, L. N. (1994). Performance measurement in a downside risk framework. *The Journal of Investing*, *3*(3), 59–64.

Stigler, G. J. (1963). Public regulation of the securities markets. *Business Law*, *19*, 721.

Tramontana, F., Westerhoff, F., & Gardini, L. (2015). A simple financial market model with chartists and fundamentalists: market entry levels and discontinuities. *Mathematics and Computers in Simulation*, *108*, 16–40.

Treynor, J. (1965). *How to rate management of investment funds*. HARVARD BUSINESS REVIEW.

Walters, C., et al. (2014). The black-litterman model in detail. Available at SSRN 1314585.

Westerhoff, F. H. (2004). Multiasset market dynamics. *Macroeconomic Dynamics*, *8*(5), 596–616.

Westerhoff, F. H., & Dieci, R. (2006). The effectiveness of keynes–Tobin transaction taxes when heterogeneous agents can trade in different markets: a behavioral finance approach. *Journal of Economic Dynamics & Control*, *30*(2), 293–322.

Westerhoff, F. H., & Reitz, S. (2003). Nonlinearities and cyclical behavior: the role of chartists and fundamentalists. *Studies in Nonlinear Dynamics & Econometrics*, *7*(4).

Wilder, J. W. (1978). *New Concepts in Technical Trading Systems*. Trend Research.

Xidonas, P., Steuer, R., & Hassapis, C. (2020). Robust portfolio optimization: a categorized bibliographic review. *Annals of Operations Research*, *292*(1), 533–552.

Yoshimoto, A. (1996). The mean-variance approach to portfolio optimization subject to transaction costs. *Journal of the Operations Research Society of Japan*, *39*(1), 99–117.

Zeeman, E. (1974). On the unstable behavior of stock exchanges. *Journal of Mathematical Economics*, *1*, 39–49.